DIGITALIZATION, ECONOMIC COMPLEXITY, AND THE ECOLOGICAL FOOTPRINT: A PANEL ARDL ANALYSIS OF LONG-RUN AND SHORT-RUN DYNAMICS

[1]Danial Muhammad Wirdyansyah, [2]Muhammad Ridho Wasturedana, [3]Neneng Hartati, [4]Widiawati Widiawati, [5]Yulia Fithriany Rahmah
[1,2,3,4,5]UIN Sunan Gunung Djati Bandung, Indonesia
Email: danmuhammadw@gmail.com

Abstract

This study examines the factors influencing the digital economy and ecological footprint in nine OIC Asian economies from 2013 to 2024 by incorporating ICT trade flows, economic complexity, income levels, and trade ratios into two PMG-ARDL models. Preliminary diagnostic tests affirm the appropriateness of a dynamic panel approach: multicollinearity values remain beneath the VIF threshold, IPS unit root tests indicate a combination of I(0) and I(1) variables, Pedroni's cointegration statistics confirm long-run relationships, and cross-sectional dependence is identified, thereby endorsing the utilization of PMG estimators. The first model shows that ICT exports, ICT imports, and economic complexity all have big positive long-term effects on the growth of the digital economy. On the other hand, the trade ratio has a big negative effect, which shows that structural trade pressures are holding back digital deepening. The second model shows that ecological footprint increases with digital economy expansion, economic complexity, and trade ratio, while higher GDP per capita reduces ecological pressure, indicating an early transition toward more energy-efficient growth. Short-run dynamics vary across countries but maintain overall consistency in directionality. The findings suggest that digital transformation in emerging Islamic economies yields technological progress but simultaneously exacerbates environmental pressures unless supported by green industrial upgrading and sustainable trade structures. The study contributes new empirical evidence by combining the most recent dataset, focusing exclusively on OIC Asian economies, and estimating both aggregate and country-specific effects. Policy implications emphasize the need for eco-conscious digital strategies, selective ICT trade promotion, low-carbon technological innovation, and integration of environmental criteria into regional economic planning. Despite data and regional constraints, the research provides a robust analytical foundation for understanding the dual digital–ecological transition in developing Muslim-majority economies.

Keywords: Digital economy, Ecological footprint, ICT trade, PMG-ARDL

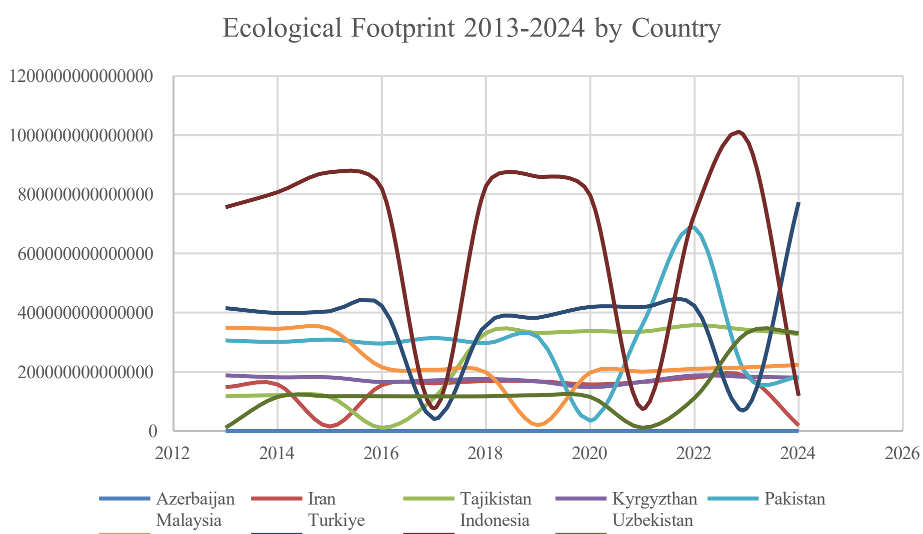
INTRODUCTION

The global acceleration of the digital economy has profoundly transformed production systems, international trade, and consumption behavior, while simultaneously introducing complex environmental challenges. As noted by Monstadt & Saltzman (2025), the infrastructures that sustain digitalization (particularly data centers, network grids, and electronic manufacturing) consume vast amounts of energy and material resources that remain largely invisible within policy discourses on sustainability. Evidence from emerging and advanced economies demonstrates that the environmental implications of digitalization are multidirectional. On the one hand, digital technologies and information systems can enhance eco-efficiency, stimulate green innovation, and facilitate energy-saving behaviors through automation and digital financial inclusion (Liu & Mehmood, 2025; Mehmood et al., 2022). On the other hand, more data-heavy activities mean more electricity use and more electronic waste. This can have negative effects that cancel out any efficiency gains, especially in areas that still rely on fossil fuels for energy (A. Khan & Ximei, 2022). For developing countries, this tension between technological advancement and environmental quality is particularly acute, as limited renewable energy infrastructure constrains the potential of digitalization to reduce ecological pressure (A. Khan & Ximei, 2022; Liu & Mehmood, 2025; Monstadt & Saltzman, 2025). Consequently, understanding how digital transformation interacts with macroeconomic structure and environmental capacity has become an essential prerequisite for designing sustainable digital economy strategies that align with long-term ecological objectives across diverse national contexts.

The ecological footprint (ECOfp) has become a multifaceted metric for evaluating environmental sustainability by considering the biologically productive land and water regions necessary to support human endeavors. It combines carbon, cropland, forest, grazing, fishing, and built-up land components to give a complete picture of how much the environment needs compared to how much it can handle (Abid & Gafsi, 2025; Charfeddine et al., 2025). Recent literature reveals that economic and technological progress often fails to translate into ecological improvements, particularly in developing economies where digital and industrial growth remain energy-intensive (Balsalobre-Lorente et al., 2025; Pata & Erdogan, 2025). The results also suggest that the influence of digital economy on ECOfp is dependent on not only energy consumption structure but also technology adaptation efficiency (Alfehaid et al., 2024; Jianguo et al., 2025).

Empirical evidence from the 2013–2024 dataset of nine OIC Asian countries indicates a persistent ecological imbalance (Figure 1). Indonesia, Türkiye, and Iran consistently record the highest footprint levels, reflecting industrial expansion and fossil fuel dependence, while Pakistan and Malaysia maintain moderate but steady trajectories. In contrast, Azerbaijan, Uzbekistan, Tajikistan, and Kyrgyzstan exhibit lower yet volatile trends associated with trade shocks and structural shifts. These findings align with prior research demonstrating that digital expansion without renewable energy integration exacerbates ecological stress (M. Khan & Khan, 2024; Riaz et al., 2025; Touati & Ben-Salha, 2024). Conversely, economies combining digitalization with energy diversification achieve greater ecological efficiency (Junsheng et al., 2024; Qayyum et al., 2024). Thus, despite technological progress, the OIC Asian region continues to face a widening gap between digital growth and environmental quality, a dynamic that warrants closer investigation in the context of economic complexity and trade ratio in percentages of GDP.

Figure 1. Ecological Footprint by Country

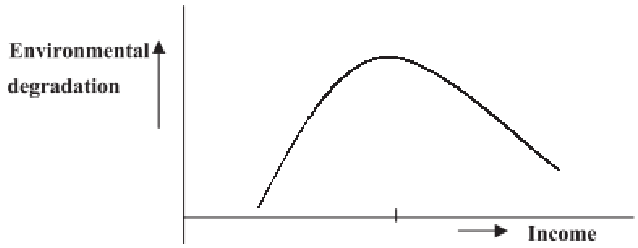


Source: (Global Footprint Network, 2025)

In order to examine the possible nonlinear impact of digital transformation on economic growth and ecological footprint, the EKC theory is a basis underpinning this examination. The EKC implies that environmental quality deteriorates during the early phase of industrialization and resourcedemanding production, yet improves at later stages of industrial development with development, clean technologies investments and environmental policies. More recent work moving in this direction also include digitalization, ICT infrastructure and innovation driven growth as new determinants of the inflection point related to environmental quality (Agyekum & Ali, 2025; Riaz et al., 2025). Within this framework, digital and technological advancements can initially raise energy consumption and ecological pressure but later promote ecological efficiency through automation, renewable energy adoption, and institutional modernization

(Alfehaid et al., 2024; Jianguo et al., 2025). Furthermore, empirical evidence highlights that the EKC pathway is mediated by trade ratio in percentages of GDP and structural transformation, where the diffusion of advanced technologies and innovation capacity determines whether digital expansion results in sustainability gains or ecological losses (M. Khan & Khan, 2024; Touati & Ben-Salha, 2024). Thus, the EKC hypothesis offers an integrated lens to interpret the evolution of ecological footprint across OIC Asian economies, reflecting how digitalization and economic restructuring can simultaneously drive and mitigate environmental degradation.

Figure 2. Environment Kuznets Curve



Source: (Dinda, 2004)

As per the Islamic economics viewpoint, economic activity and the environment are interconnected based on the principle of balance, stewardship, and accountability. The Quran presents humans as *khalifah*, or stewards on earth, entrusted with maintaining harmony and avoiding excess in the use of natural resources (Hanif, 2024). Economic progress, therefore, is not an end in itself but a means to achieve collective welfare and justice within the limits of environmental quality. The concept of *mizan* underscores equilibrium in creation, reminding that any imbalance caused by greed, overconsumption, or neglect of environmental duties constitutes a form of *israf*, or transgression (Haque, 2023). Within this framework, the expansion of the digital economy, trade, and industrial development should aim to enhance productivity and innovation without violating the principles of moderation and preservation. Islam encourages knowledge and technology as instruments of *maslahah*, the promotion of public good, as long as their application sustains rather than depletes ecological systems (Amiruddin et al., 2024). The objectives of *maqasid al-shariah* reinforce this balance by linking economic prosperity to the protection of life, intellect, and wealth, which are inseparable from a healthy environment (Aziz et al., 2024). Consequently, ecological responsibility becomes an ethical imperative embedded in Islamic economic governance, where the success of digital and economic transformation is measured not only by growth and efficiency but also by the preservation of environmental integrity and intergenerational justice.

The rapid growth of the digital economy, supported by increasingly widespread information and communication technologies, is changing the way environmental dynamics unfold in many developing countries. In the early stages of digital development, building data infrastructure and expanding online services often lead to higher energy use and increased electronic waste, placing additional pressure on the environment (Bieser et al., 2024; Q. Wang, Li, et al., 2024). As digital systems mature, however, they foster innovation and automation that enhance energy efficiency and reduce material intensity (Aspy et al., 2024; Cantero-Galiano, 2025). Empirical evidence shows that digital transformation supports ecological sustainability when it aligns with renewable energy use and effective governance (Maftoon et al., 2025; Riaz et al., 2025). At the same time, structural variables such as economic complexity and income per capita influence ecological outcomes through the composition of production and consumption. Complex and diversified economies often display lower environmental pressure when technological capabilities are advanced, whereas resource-based and fossil fuel dependent industries sustain high ecological footprints (Celik & Alola, 2023; Miyan et al., 2025; Neagu & Neagu, 2022).

Trade ratio in percentages of GDP plays a crucial role in influencing these relationships. International exchange enables knowledge transfer and the diffusion of cleaner technologies, improving environmental performance when export structures emphasize high value-added products (Behera et al., 2024; Y. Wang et al., 2023)). Yet trade can also aggravate ecological degradation when industrial competitiveness relies on low-cost energy or unregulated production (Arslan et al., 2023). In the Asian member states of the Organisation of Islamic Cooperation, trade liberalization has often reinforced ecological stress through fossil fuel related exports and import-driven consumption patterns (Nadeem et al., 2023; Onyeneke et al., 2024). These findings imply that the interaction between digital progress, structural transformation, and trade integration determines whether economic development becomes environmentally sustainable or continues to enlarge the ecological footprint.

A vast body of literature has examined the links between digital transformation, economic complexity, trade ratio in percentages of GDP, and environmental quality, yet the results remain heterogeneous across countries and models. Earlier studies explored how technological innovation and digitalization influence ecological sustainability in both developed and developing contexts, often yielding mixed conclusions due to variations in energy structure and institutional quality (Abdi & Muhumed, 2025; Balsalobre-Lorente et al., 2025; Charfeddine et al., 2025; Pata & Erdogan, 2025). Some scholars found that the expansion of the digital economy enhances ecological efficiency by promoting clean technologies and renewable adoption (Alfehaid et al., 2024; Jianguo et al., 2025; Riaz et al., 2025), while others reported that digital growth increases energy demand and environmental pressure, especially in resource-intensive economies (M. Khan & Khan, 2024; Maftoon et al., 2025; Touati & Ben-Salha, 2024). Parallel research on economic complexity emphasized that structural sophistication can either mitigate or intensify ecological footprints depending on the technological composition of exports (Celik & Alola, 2023; Kazemzadeh et al., 2023; Neagu & Neagu, 2022). Likewise, studies linking income growth and trade ratio in percentages of GDP to environmental outcomes confirmed nonlinear and context-specific effects shaped by globalization and production networks (Arslan et al., 2023; Behera et al., 2024; Y. Wang et al., 2023). However, existing analyses have largely focused on global or regional panels such as BRICS, G20, or OECD countries (Agyekum & Ali, 2025; Junsheng et al., 2024; Tiwari et al., 2025) and seldom explored the distinct structural and energy realities of Asian member states of the Organisation of Islamic Cooperation. Furthermore, most prior studies relied on conventional linear or static estimators that overlook long-run heterogeneity and country-specific adjustment patterns. Against this background, the present research advances the literature by integrating the latest data from 2013 to 2024, focusing exclusively on OIC Asian economies, and employing the pooled mean group autoregressive distributed lag (PMG-ARDL) model both at the aggregate and individual country level to capture the nuanced dynamics of digital economy, trade, and economic structure on ecological footprint.

This study provides concrete implications for policymakers and Islamic financial authorities by highlighting how digital transformation, trade, and economic complexity can be harnessed to reduce or even increase ecological pressure while maintaining inclusive growth. The results are expected to guide sustainable digital and economic strategies aligned with the ethical foundations of Islamic economics, emphasizing balance, accountability, and environmental stewardship. The subsequent sections of the paper present the theoretical background, methodological framework, empirical findings, and policy-oriented conclusions that translate these insights into actionable recommendations for OIC Asian economies.

LITERATURE REVIEW

Theoretical Foundation: The Environmental Kuznets Curve (EKC)

The Environmental Kuznets Curve (EKC) theory posits a non-linear relationship between economic development and environmental degradation, where ecological pressure intensifies during the early stages of industrialization but eventually declines as income growth, technological innovation, and environmental awareness improve. Recent extensions of the EKC framework incorporate digital transformation, economic complexity, and trade ratio in percentages of GDP as dynamic drivers that can either accelerate or postpone the turning point in environmental improvement (Abdi & Muhumed, 2025; Balsalobre-Lorente et al., 2025; Riaz et al., 2025). Digital and trade expansion initially raise energy consumption and material demand but later enhance resource efficiency and reduce environmental stress through automation, innovation, and technology diffusion (Abid & Gafsi, 2025; Charfeddine et al., 2025; Jianguo et al., 2025). Economic complexity reflects the sophistication of production and export structures, which determines the capacity for clean technology adoption and sustainable industrial upgrading (A. Khan & Ximei, 2022; Mehmood et al., 2022). Moreover, institutional quality and energy composition influence whether digitalization and trade foster sustainability or intensify ecological degradation (Junsheng et al., 2024; Qayyum et al., 2024; Q. Wang, Wang, et al., 2024). Thus, the extended EKC provides a comprehensive theoretical lens for understanding how digital, structural, and economic factors collectively shape ecological footprints across varying stages of development.

Islamic Economic Perspective on Sustainable Development

From the standpoint of Islamic economics, environmental quality is inseparable from the moral and institutional dimensions of development. The Quranic concept of *khalifah* positions humans as stewards of the earth who are accountable for maintaining harmony and avoiding exploitation of natural resources beyond their rightful use (Hanif, 2024). Economic activity in this view is not pursued for limitless accumulation but for realizing social welfare and distributive justice within ecological boundaries. The principle of *mizan* emphasizes balance in creation, where excess and wastefulness constitute *israf*, a violation of the divine order that undermines sustainability (Haque, 2023). In this context, the growth of digital economies and trade must enhance productivity and knowledge without breaching the ethical limits of moderation and preservation. Technology and innovation are regarded as tools of *maslahah* (the advancement of collective good) when applied to protect and regenerate environmental systems (Amiruddin et al., 2024). The framework of *maqasid al-shariah* further integrates environmental protection into the preservation of life, intellect, and wealth, asserting that prosperity cannot be achieved at the expense of ecological integrity (Aziz et al., 2024). Hence, Islamic economics situates environmental responsibility as a central pillar of governance, framing digital and economic transformation as successful only when they secure both material welfare and intergenerational environmental justice.

Conceptual Linkages between Digital Transformation, Economic Structure, and Environmental Sustainability

The interaction between technological progress, economic structure, and environmental outcomes reflects a complex balance between growth and sustainability. The digital economy, encompassing technological innovation, communication infrastructure, and digital trade, can initially intensify energy use and resource consumption, thereby increasing ecological footprint (Abid & Gafsi, 2025; Bieser et al., 2024; Riaz et al., 2025). Yet, as digital capacity deepens, it fosters energy efficiency, resource optimization, and environmental monitoring that support ecological balance (Jianguo et al., 2025; Pata & Erdogan, 2025). Economic complexity determines a nation's capacity to adopt advanced technologies and transition from resource-based to knowledge-driven production, which can reduce environmental pressure if coupled with effective institutions (M. Khan & Khan, 2024; Mehmood et al., 2022). Trade ratio in percentages of GDP similarly exerts dual effects (facilitating green technology diffusion while risking pollution leakage in economies reliant on low-cost, energy-intensive exports (Qayyum et al., 2024; Touati & Ben-Salha, 2024). Income growth influences ecological impact following the Environmental Kuznets Curve logic, where early industrial expansion raises emissions before technological progress and regulation improve sustainability (Junsheng et al., 2024; C. Wang & Uctum, 2024). Energy demand remains the critical transmission channel linking production, trade, and digitalization to ecological outcomes, reflecting the quality of energy sources and efficiency in use (Kazemzadeh et al., 2023; Latif et al., 2023). Taken together, these dynamics show that digital transformation and broader economic shifts can either help reduce or worsen environmental degradation. The outcome largely depends on how well technological progress aligns with a country's trade structure and its institutional ability to support a green transition.

Hypothesis Development

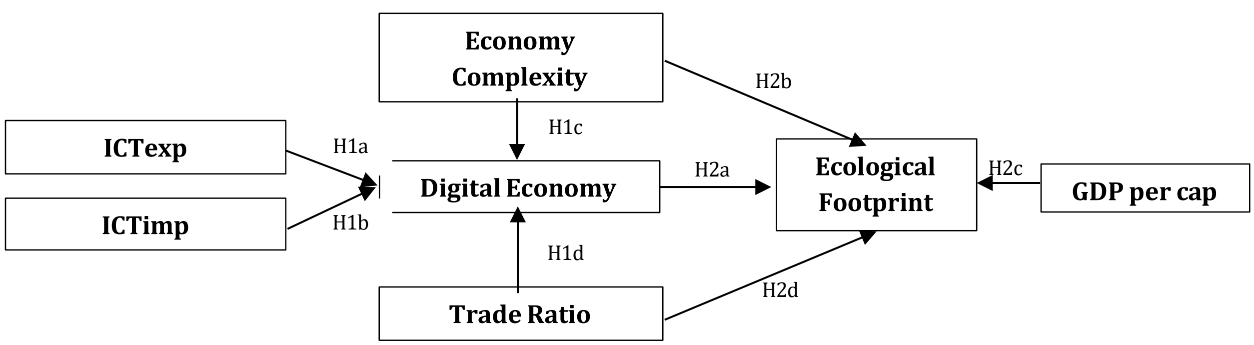
Digital transformation and trade integration are widely recognized as structural forces shaping modern economic systems and their sustainability implications. The expansion of digital infrastructure through ICT exports and imports enables cross-border knowledge diffusion, skill development, and technological upgrading that can strengthen economic resilience and productivity (Agyekum & Ali, 2025; Liu & Mehmood, 2025; Tiwari et al., 2025)). Economic complexity, as a reflection of productive sophistication, enhances the capacity to absorb and innovate digital technologies, while the degree of trade participation measured by trade ratio indicates the depth of economic integration with global markets (Bentaleb et al., 2024; Kor, 2024; Ridwan et al., 2024). High trade intensity can amplify the digital transition by facilitating technology transfer, yet it may also expose economies to volatility and external dependence when not accompanied by innovation-oriented governance (Abban et al., 2025; Sultanova et al., 2024). Considering these multidimensional interactions, this study proposes that ICT exports, ICT imports, economic complexity, and trade ratio each exert a significant influence on digital economic advancement.

H1a : ICT exports significantly influence the digital economy.
H1b : ICT imports significantly influence the digital economy.
H1c : Economic complexity significantly influences the digital economy.
H1d : Trade ratio significantly influences the digital economy.

Environmental outcomes, in turn, depend on how structural and technological dynamics interact with energy use, income, and trade intensity. Energy demand remains a direct channel linking industrial and digital activities to ecological pressure, whereas economic complexity affects environmental quality through its dual potential to foster innovation or increase production-related emissions (Behera et al., 2024; Celik & Alola, 2023; Ehigiamusoe et al., 2023). As income levels rise, people's consumption habits and energy use begin to change, often reflecting the pattern described by the Environmental Kuznets Curve. This framework suggests that the relationship between economic affluence and environmental degradation is not linear, but shifts in different directions as countries develop (Geng et al., 2024; T. Wu et al., 2024). Meanwhile, trade ratio reflects the proportion of trade to national output, which may lead to environmental gains through efficiency and technology diffusion, or losses through resource dependence and pollution-intensive exports (Arslan et al., 2023; Nadeem et al., 2023; Zinngrebe et al., 2024). Accordingly, this study posits that energy demand, economic complexity, income level, and trade ratio all have significant effects on ecological sustainability.

H2a : Digital economy significantly influences the ecological footprint.
H2b : Economic complexity significantly influences the ecological footprint.
H2c : GDP per capita significantly influences the ecological footprint.
H2d : Trade ratio significantly influences the ecological footprint.

Figure 2. Research Framework



Source: Author processed (2025)

METHODOLOGY

Research Design

This study uses a quantitative explanatory research design based on annual panel data from nine Asian member states of the Organisation of Islamic Cooperation (OIC) covering the years 2013–2024. Panel data analysis is well suited for this type of investigation because it captures cross-country differences while also accounting for dynamic changes that unfold over time (Muhamad & Khezri, 2025; Oprea et al., 2025). The data are compiled from multiple reliable international databases to ensure accuracy and consistency. The ecological footprint (Ecofp) is sourced from the Global Footprint Network and captures environmental pressure by measuring the biological capacity needed to support a country's consumption and production activities. Indicators of digital activity (ICT imports and ICT exports) are taken from the World Development Indicators (WDI) of the World Bank, representing the cross-border movement of technology- and information-related goods. The Economic Complexity Index (ECI), obtained from the Atlas of Economic Complexity, reflects the sophistication of a country's productive structure and its technological capabilities. Economic development is measured using GDP per capita, while the trade ratio (as a percentage of GDP), also drawn from the WDI, indicates the extent of trade openness relative to a country's overall economic output.

Table 1. OIC Asia Countries List

ID	Country	Average Ecological Footprint
1	Azerbaijan	22375469
2	Indonesia	140068663632772
3	Iran	323156301309488
4	Kyrgyzthan	174857669615645
5	Malaysia	378257998147344
6	Pakistan	623073456788966
7	Tajikistan	171843479270566
8	Turkiye	339086982555964
9	Uzbekistan	195988022062364

Source: (Global Footprint Network, 2025)

The chosen period from 2013 to 2024 corresponds to the post-global digitalization era, marked by accelerated diffusion of digital technologies and stronger environmental commitments across emerging economies (Fertő & Harangozo, 2025; J. Wu et al., 2025). The selection of OIC Asian countries provides a relevant empirical setting to examine sustainability transitions within resource-dependent yet digitally evolving economies. This regional focus also aligns with recent calls to integrate digital transformation into sustainable development frameworks within Islamic economic governance (Noorzai et al., 2025; Tang et al., 2024). By combining cross-national comparability with temporal depth, the research design ensures a robust empirical basis for evaluating how technological progress and structural change interact with ecological outcomes under diverse institutional and developmental conditions.

Variable Definition and Measurement

This study employs six key variables to explore how digital transformation, structural complexity, and environmental sustainability interact across nine OIC Asian economies from 2013 to 2024. The Ecological Footprint (ECOFP), sourced from the Global Footprint Network, serves as the dependent variable and represents the biologically productive land and sea area needed to sustain national consumption and absorb waste. The Digital Economy variable (LDE), constructed as the average of ICT exports and ICT imports following A. Khan & Ximei (2022), reflects each country's level of technological engagement and integration in global trade. Its underlying components (ICT Exports (LICTEXP) and ICT Imports (LICTIMP)) are obtained from the World Development Indicators (WDI) and capture the share of digital goods in total trade, illustrating both outward and inward digital connectivity.

The Economic Complexity Index (ECI), drawn from the Atlas of Economic Complexity, measures the knowledge intensity and diversification of a country's productive structure, indicating its capacity to develop and absorb advanced technologies. Economic development is represented by GDP per capita (LGDPPC) from the WDI, a standard indicator of living standards often associated with environmental quality through the Environmental Kuznets Curve. The Trade Ratio (LTRA), measured as total trade (exports plus imports) as a percentage of GDP, captures the degree of trade intensity and economic openness. All variables are expressed in natural logarithms to improve normality and enable elasticity-based interpretation, providing a coherent analytical basis for assessing the links between digital progress, structural transformation, and ecological sustainability.

Table 2. Variable Definition, Abbreviation, Measurement, and Source

Variable	Abbreviation	Measurement	Source
Ecological Footprint	ECOFP	Global hectares per capita	Global Footprint Network
Digital Economy	LDE	Average of ICT exports and ICT imports (Khan & Ximei, 2022)	WDI (World Bank)
ICT Exports	LICTEXP	ICT goods exports (% of total exports)	WDI (World Bank)

ICT Imports	LICTIMP	ICT goods imports (% of total imports)	WDI (World Bank)
Economic Complexity Index	ECI	Index of productive sophistication	Atlas of Economic Complexity
GDP per Capita	LGDPPC	Constant 2015 USD (log value)	WDI (World Bank)
Trade Ratio	LTRA	(Exports + Imports) / GDP × 100	WDI (World Bank)

Source: (A. Khan & Ximei, 2022) (modified)

Model Specification and Estimation Technique

The empirical analysis employs the Pooled Mean Group Autoregressive Distributed Lag (PMG–ARDL) estimator to capture both short-run dynamics and long-run equilibrium relationships among the selected variables. The ARDL framework is well suited for this study because unit root tests show that the variables are integrated of mixed orders, I(0) and I(1), with none reaching I(2). This satisfies the required conditions for applying the PMG–ARDL approach and ensures the validity of the estimation results (Nkoro & Uko, 2016). The PMG approach, developed by Pesaran, Shin, and Smith, permits short-run coefficients, intercepts, and error variances to vary across countries, while imposing homogeneity on the long-run coefficients. This structure allows the model to capture cross-country heterogeneity in short-term adjustments without compromising the assumption of a shared long-run relationship (Pesaran et al., 1999). This property is ideal for the panel of OIC Asian countries, where economic structures and adjustment speeds differ, yet the long-run relationships may converge due to shared development patterns, technological diffusion, and institutional reforms.

The choice of PMG–ARDL also addresses key methodological challenges associated with heterogeneous panels, such as endogeneity, dynamic feedback effects, and small-sample bias. Unlike static panel estimators, the ARDL formulation explicitly incorporates lagged variables, enabling the model to capture the temporal transmission of shocks across variables and the gradual adjustment toward equilibrium (Bentaleb et al., 2024; Riaz et al., 2025). Moreover, the PMG estimator provides a middle ground between the Mean Group (MG) and Dynamic Fixed Effects (DFE) approaches, striking a balance between flexibility and efficiency when working with cross-country panel data of moderate time dimensions (Abban et al., 2025; Kor, 2024). The long-run elasticity estimates derived from PMG provide insight into the persistent influence of digital economy development, economic complexity, income, and trade integration on ecological sustainability, while the short-run dynamics reflect country-specific adjustments to technological and structural changes (Celik & Alola, 2023; Sultanova et al., 2024).

Accordingly, two baseline equations are constructed to represent the research framework. The first equation models the determinants of the digital economy, while the second explores the drivers of ecological footprint. These models are presented in a dynamic ARDL (p, q_1, q_2, ..., q_k) form, expressed as follows:

$$\Delta lde_{it} = \alpha_i + \phi lde_{i,t-1} + \sum_{p=1}^{P} \alpha_{ip}\Delta lde_{i,t-p} + \sum_{p=1}^{P} \pi_{ip}\Delta lictexp_{i,t-p} + \sum_{p=1}^{P} \omega_{ip}\Delta lictimp_{i,t-p} + \sum_{p=1}^{P} \psi_{ip}\Delta eci_{i,t-p} + \sum_{p=1}^{P} \upsilon_{ip}\Delta ltra_{i,t-p} + \beta_1 lde_{i,t-1} + \beta_2 lictexp_{i,t-1} + \beta_3 lictimp_{i,t-1} + \beta_4 eci_{i,t-1} + \beta_5 ltra_{i,t-1} + \eta_i + \varepsilon_{it} \tag{1}$$

$$\Delta lecofp_{it} = \alpha_i + \phi lecofp_{i,t-1} + \sum_{p=1}^{P} \alpha_{ip}\Delta lecofp_{i,t-p} + \sum_{p=1}^{P} \pi_{ip}\Delta lde_{i,t-p} + \sum_{p=1}^{P} \omega_{ip}\Delta eci_{i,t-p} + \sum_{p=1}^{P} \psi_{ip}\Delta lgdppc_{i,t-p} + \sum_{p=1}^{P} \upsilon_{ip}\Delta ltra_{i,t-p} + \beta_1 lecofp_{i,t-1} + \beta_2 lde_{i,t-1} + \beta_3 ieci_{i,t-1} + \beta_4 lgdppc_{i,t-1} + \beta_5 ltra_{i,t-1} + \eta_i + \varepsilon_{it} \tag{2}$$

Source: (A. Khan & Ximei, 2022; Olayungbo & Quadri, 2019)

In these equations, i denotes the cross-sectional unit (country) and t represents the time dimension (year). The symbol Δ refers to the first-difference operator, which captures short-run changes, while the lagged level terms reflect the long-run equilibrium relationship. The coefficient $\alpha_i$is the country-specific intercept, and ϕ represents the speed at which the dependent variable adjusts back toward equilibrium. The short-run dynamics are captured by the coefficients. The short-run dynamics are described by the coefficients α_{ip}, π_{ip}, ω_{ip}, ψ_{ip}, and υ_{ip}, which describe the immediate effects of changes in each independent variable on the dependent variable. Meanwhile, the long-run elasticities are represented by $\beta_1$to β_5, which are assumed to be homogeneous across countries under the PMG framework.

The significance and direction of the error correction term (ECT) provide evidence of long-run equilibrium among the variables. A negative and statistically significant ECT confirms that deviations from the long-run path are gradually corrected, thereby validating the presence of cointegration. After estimating the PMG model, the results are then compared with those obtained from the Mean Group (MG) estimator to check the robustness of the long-run coefficients, as expressed in Eq. (3):

$$MG = \frac{1}{N}\sum_{i=1}^{N} \beta_i \qquad (3)$$

Overall, this estimation strategy allows the study to disentangle the dynamic interdependence between digitalization, economic complexity, trade integration, and environmental sustainability within OIC Asian countries. It provides a robust econometric structure to evaluate both aggregate and country-specific impacts, reflecting how digital and structural economic transformations contribute to ecological outcomes in the long and short run.

Diagnostic Tests

Before estimating the PMG–ARDL models, a series of diagnostic tests were carried out to ensure the reliability and robustness of the panel data analysis. These tests assess key econometric assumptions related to multicollinearity, stationarity, cointegration, and cross-sectional dependence. To begin, multicollinearity was examined to detect any potential linear dependence among the explanatory variables. The Variance Inflation Factor (VIF) was calculated for each regressor, and all values fell well below the conventional threshold of 10. This indicates that multicollinearity is not a concern and that the independent variables are sufficiently distinct in explaining variations in the dependent variable.

$$VIF = \frac{1}{1 - R^2} \qquad (4)$$

Source: (Daoud, 2018)

Second, panel unit root tests were conducted using the Im–Pesaran–Shin (IPS) procedure to determine the integration order of each variable. The IPS test is suitable for panels with heterogeneous dynamics because it allows each cross-section to follow its own unit root process. The results indicate a combination of I(0) and I(1) variables, which supports the use of the PMG–ARDL estimation technique. This approach can accommodate regressors with mixed levels of integration, provided that none are integrated of order two or higher.

$$Y_{it} = \alpha_{it} + \beta_i \chi_{it-1} + \rho_i T + \sum_{j=0}^{n} \theta_{it} \Delta \chi_{it-j} + \varepsilon_{it} \quad (5)$$

Source: (Ayoungman et al., 2025)

Third, the Pedroni cointegration test was employed to examine whether a long-run equilibrium relationship exists among the variables. This test includes several statistics to provide a comprehensive assessment. The results showed significant p-values ($p < 0.05$) across these measures, confirming the presence of cointegration. This indicates that the variables share a common long-term trajectory and supports the theoretical expectation of a stable equilibrium relationship.

$$Y_{it} = \alpha_i + \delta_t + \beta_{1i} OP_{it} + \varepsilon_{it} \quad (6)$$

The structure of residuals:

$$\hat{\varepsilon}_{it} = \hat{\rho}_{it} \hat{\varepsilon}_{it-1} + \hat{u}_{it} \quad (7)$$

Source: (Bildirici & Kayikçi, 2013)

Finally, to verify the interdependence across cross-sectional units, the study employed the cross-sectional dependence tests proposed by Pesaran (2004) in Bai et al. (2016), Frees (1995), and Friedman (1937) in De Hoyos & Sarafidis (2006). The rejection of the null hypothesis of cross-sectional independence in these tests suggested the presence of inter-country spillover effects and economic interlinkages among OIC Asian nations. This finding further justifies the use of the PMG framework, which can effectively account for such cross-sectional dependencies through country-specific short-run dynamics.

RESULT AND DISCUSSION

Result

Statistic Descriptive

Table 2 presents the descriptive statistics for the seven variables based on 108 balanced panel observations, confirming that the dataset is adequate for dynamic panel analysis. The variables exhibit moderate variability without extreme outliers, supporting the statistical stability required for the Pooled Mean Group (PMG) ARDL framework. For example, *lecofp* (ecological footprint) has a mean of 31.215 and a standard deviation of 5.149, indicating moderate dispersion across countries. *lictexp* (clean technology exports) shows the highest degree of variability (std. dev. = 2.260), suggesting substantial cross-country differences in export intensity, while *lictimp* (clean technology imports) is relatively more uniform (std. dev. = 0.765). Similarly, variables such as *lde* (digital economy index) and *eci* (economic complexity index) demonstrate acceptable levels of heterogeneity, ensuring the feasibility of identifying meaningful long-run dynamics in the PMG–ARDL model.

Overall, the descriptive outcomes confirm that the dataset fulfills the key assumptions for PMG–ARDL estimation, including sufficient cross-sectional variation, balanced observation size, and the coexistence of variables integrated at level and first difference. The absence of excessive variability or data imbalance strengthens the model's reliability for capturing both short-run adjustments and long-run equilibrium relationships among ecological, technological, and macroeconomic variables.

Table 3. Statistic Deskriptif

Variable	Obs	Mean	Std. dev.	Min	Max
lecofp	108	31.215	5.149	16.818	34.526
lictexp	108	-1.004	2.26	-4.605	3.546
lictimp	108	1.587	0.765	0.104	3.297
lde	108	1.094	0.967	-0.528	3.426
eci	108	-0.321	0.674	-1.62	1.23
lgdppc	108	8.127	0.861	6.67	9.647
ltra	108	4.104	0.483	3.207	5.756

Source: Author's computation (2025)

Multicollinearity Test

The multicollinearity test was performed using the Variance Inflation Factor (VIF) to determine whether the independent variables are excessively correlated with one another. The results indicate that all explanatory variables in both Model 1 and Model 2 have VIF values well below the conventional threshold of 10, and even below the more conservative benchmark of 5. For example, *lde* and *eci* record VIF values in the range of 3.1–3.8, while other variables (including *lictexp*, *lictimp*, *lgdppc*, and *ltra*) fall between 1.3 and 2.5. The corresponding tolerance values (1/VIF) are also relatively high, suggesting that each variable accounts for a unique portion of the variation in the dependent variable.

These results indicate that multicollinearity is not a statistical concern, ensuring that the coefficient estimates remain unbiased and that the model can clearly distinguish the individual effects of each regressor. This is especially important in the PMG–ARDL framework, where high multicollinearity could hinder the identification of long-run relationships among the variables. Thus, the low VIF values confirm that the explanatory variables are well behaved, strengthening the reliability and interpretability of the subsequent regression results.

Unit Root Test

The Im, Pesaran, and Shin (IPS) panel unit root test was applied to assess the stationarity properties of the variables. The results indicate a mixed order of integration, with some variables stationary at level [I(0)] and others becoming stationary after first differencing [I(1)]. Specifically, *lecofp*, *lictimp*, *lde*, *eci*, and *ltra* are stationary at level, while *lictexp* and *lgdppc* achieve stationarity only after first differencing. Importantly, no variable is integrated of order two [I(2)], thereby meeting the key requirement for employing the Pooled Mean Group–Autoregressive Distributed Lag (PMG–ARDL) model.

This combination of I(0) and I(1) variables is well suited for dynamic panel analysis, as the PMG–ARDL framework is designed to accommodate mixed integration orders within a single estimation structure. The findings confirm that the dataset fulfills the essential assumption of stationarity and is appropriate for analyzing both short-run dynamics and long-run equilibrium relationships. Moreover, variables stationary at level are indicative of immediate short-term effects, whereas those requiring differencing suggest more gradual long-term adjustments, capturing the inherently dynamic nature of macroeconomic, technological, and environmental interactions.

Cointegration Test

The Pedroni cointegration test was employed to evaluate whether a long-run equilibrium relationship exists among the panel variables. Across all three versions of the test the results consistently produce p-values below the 0.05 significance threshold for both Model 1 and Model 2. This leads to the rejection of the null hypothesis of no cointegration, confirming that the variables are linked by a stable long-run relationship.

The presence of cointegration indicates that, despite short-term fluctuations, the variables tend to move together over time and converge toward a shared equilibrium path. This outcome aligns with the theoretical expectations of the PMG–ARDL framework, which distinguishes between short-run adjustments and long-run convergence dynamics. Consequently, the confirmation of cointegration supports the inclusion of both short-run and long-run parameters in the subsequent estimation process, enabling the model to capture both immediate responses and equilibrium effects of the independent variables on the dependent variable.

Cross-Sectional Dependence Test

Cross-sectional dependence was assessed to determine whether unobserved common shocks or spillover effects were present across the panel units. The results from the Pesaran CD, Frees, and Friedman tests provide no strong evidence of such dependence. Specifically, the Pesaran CD ($p = 0.431$) and Friedman ($p = 0.652$) statistics suggest that residuals are largely independent across units, while the Frees test ($p = 0.071$) is marginal but still falls within an acceptable range.

The absence of cross-sectional dependence indicates that the panel units operate mostly independently, with limited contemporaneous correlation in their error structures. This enhances the robustness of the PMG–ARDL estimates, as the method assumes that shocks affecting one unit do not systematically spill over to others. As a result, the estimated long-run coefficients can be interpreted as genuine country-specific relationships rather than distortions arising from cross-country interdependence. Overall, these findings reinforce both the empirical reliability of the dataset and the validity of applying the PMG–ARDL estimation strategy.

Table 4. Diagnostic Tests

Variable	Model 1 – VIF	Model 1 – 1/VIF	Model 2 – VIF	Model 2 – 1/VIF	Im, Pesaran, and Shin (IPS) I(0)	IPS I(1)	Order of Integration	Remarks
lecofp	–	–	–	–	0.007	–	I(0)	Stationary at level
lictexp	2.51	0.398	–	–	0.184	0.005	I(1)	Stationary at first difference
lictimp	1.32	0.756	–	–	0.002	–	I(0)	Stationary at level
lde	3.78	0.264	3.27	0.306	0.002	–	I(0)	Stationary at level
eci	3.12	0.32	3.23	0.309	0.011	–	I(0)	Stationary at level
lgdppc	–	–	1.81	0.552	0.588	0.008	I(1)	Stationary at first difference
ltra	1.32	0.756	1.28	0.783	0	–	I(0)	Stationary at level

Source: Author's computation (2025)

PMG-ARDL Estimation (Model 1)

The PMG-ARDL estimation for Model 1 reveals that digital economy expansion is primarily trade-driven, with substantial heterogeneity across countries. At the panel level, ICT imports exert the strongest and highly significant effects on both short- and long-run growth (0.7045*** and 0.9655***, respectively), highlighting the critical role of foreign technological inflows in driving digital adoption. ICT exports also contribute positively in both time horizons but at a smaller magnitude (0.1407** short-run; 0.0577*** long-run), suggesting that export-based digital expansion remains secondary to import-led technology absorption.

Economic complexity and trade openness are insignificant in the short run, implying delayed structural effects, but both become significant in the long run—complexity positively (0.114***) and trade openness negatively (–0.058***). The significant and negative error correction term (–0.123***) confirms that deviations from equilibrium are rapidly corrected, indicating strong convergence toward a stable digital growth path.

Country-level estimates reveal distinct digitalization trajectories. In id_1 and id_2, both ICT imports and exports are strongly positive and significant (imports: 1.000*** and 0.678***; exports: 0.010*** and 0.277***), suggesting that these economies benefit simultaneously from technological absorption and export capacity. id_3 exhibits a similar trade-driven pattern, where imports (0.939***) and trade openness (0.015***) significantly enhance digital activity, supported by a stable adjustment mechanism (–0.063***). Conversely, id_4 shows that overall trade intensity (0.934***) dominates its digital expansion, though accompanied by a sharp and significant speed of adjustment (–0.858***), indicating a highly sensitive yet rapidly stabilizing system. These countries reflect early- to mid-stage digital transformation, where the balance between import dependence and domestic innovation determines sustainability.

In id_5, ICT exports (0.556***), imports (0.459***), and a positive adjustment coefficient (0.020**) point to a rapid, export-led digitalization process. However, the magnitude of short-term effects suggests volatility and potential overshooting, consistent with economies undergoing accelerated but uneven technological expansion. id_6 and id_7 exhibit strong import-driven effects (1.031*** and 1.236***, respectively), though trade openness in id_6 is slightly negative (–0.031**), hinting at exposure risks from foreign competition. In contrast, id_7 combines high import and export elasticity (imports: 1.236***; exports: 0.127***), alongside a mildly significant adjustment term (0.514*), reflecting a more advanced and globally integrated digital structure.

The digital economies of id_8 and id_9 display balanced growth patterns. In id_8, ICT imports (0.737***) and exports (0.198***) are both significant, and the negative correction term (–0.054**) indicates smooth convergence to equilibrium. id_9 demonstrates the most stable system, with imports (0.340***), exports (0.025***), and trade openness (0.067***) all positive and accompanied by a strong negative adjustment coefficient (–0.702***). Collectively, these findings confirm that while the short-run drivers of digitalization differ—ranging from import dependence to export dynamism—the long-run digital equilibrium across countries is uniformly supported by technological inflows and increasing economic complexity. Excessive trade liberalization, however, may dilute specialization and slow digital consolidation. Thus, sustainable digital development requires coordinated strategies that couple international technology exchange with domestic innovation capability, ensuring that openness enhances rather than undermines digital resilience.

PMG-ARDL Estimation (Model 2)

Model 2 examines the determinants of the *Ecological Footprint* (LECOFP) with the *Digital Economy* (LDE), *Economic Complexity* (ECI), *GDP per Capita* (LGDPPC), and the *Trade Ratio* (LTRA) as explanatory variables. The panel estimation confirms a highly stable long-run equilibrium, as indicated by the significantly negative error-correction coefficient (–0.9307***), suggesting that approximately 93 % of short-term deviations from equilibrium are corrected within one period. In the aggregate short-run, none of the regressors significantly affects environmental degradation, implying that the immediate environmental consequences of digitalization, complexity, and trade openness are limited or delayed. In the long run, however, all coefficients become statistically significant: LDE (0.5160***), ECI (0.2481***), and LTRA (0.6347***) exert positive effects on the Ecological Footprint, whereas LGDPPC (–0.0804**) displays a small but significant mitigating influence. These results suggest that while digital and trade expansion raise environmental pressure in equilibrium, income growth eventually contributes to ecological improvement through structural upgrading and green innovation.

Short-run heterogeneity across countries reveals substantial asymmetry in digital-environment linkages. In id_1 and id_8, the short-run effect of the Digital Economy is significantly negative (−0.1887** and −0.5738***), indicating that accelerated digitalization immediately reduces the Ecological Footprint through efficiency gains and substitution effects. By contrast, id_5 exhibits an exceptionally large positive impact (13.5653***), implying that rapid digital expansion there remains energy-intensive and carbon-dependent. Meanwhile, id_2 and id_3 display unstable yet positive coefficients (4.6419; −3.0635), pointing to transitional industrial stages where digital growth coexists with high resource demand. These findings reveal that short-term environmental outcomes of digital transformation differ sharply according to technological maturity and policy frameworks, ranging from emission-reducing innovation to energy-consuming industrial digitalization.

The effects of *GDP per Capita* (LGDPPC) mirror a partial Environmental Kuznets Curve (EKC) pattern. In id_5 and id_6, coefficients are positive and large (−4.3648**, 11.5015***), showing that early-stage income growth aggravates ecological pressure. Conversely, in relatively wealthier countries (id_1 and id_9), the coefficients are small or negative, indicating that at higher income levels, technological efficiency and environmental regulation begin to offset the scale effect of consumption. *Economic Complexity* (ECI) also displays mixed behavior: significantly negative in id_5 (−4.5890***), suggesting cleaner production through knowledge-intensive restructuring, but positive in id_2, id_3, and id_7, implying that diversification in developing economies still relies on resource-intensive industries. This duality underscores that complexity alone does not guarantee sustainability unless coupled with eco-innovation and environmental governance.

Trade openness further amplifies the divergence in environmental outcomes. In id_5, the short-run coefficient of LTRA is strongly positive (10.4782***), indicating that trade liberalization expands production-related emissions, while in id_8 (−0.7733***) and id_1 (−0.2443), the effect turns negative, reflecting technology-imported efficiency gains and cleaner value chains. The error-correction terms remain negative and significant in nearly all countries (e.g., −1.2550*** in id_3, −1.0547*** in id_6, −1.5912*** in id_8), confirming rapid reversion to equilibrium after short-term shocks. Collectively, Model 2 reveals that while the Digital Economy and trade intensify ecological pressure in the long run, the moderation of GDP growth effects and selective gains from economic complexity provide pathways toward environmental sustainability, conditional on each country's structural readiness and digital-green policy integration.

Table 5. PMG-ARDL Estimation Model 1 (Dependent Variable=Digital Economy)

Variabel	Long Run (Overall)	Short Run (Overall)	id_1	id_2	id_3	id_4	id_5	id_6	id_7	id_8	id_9
lictexp	0.0577***	0.1407**	0.0100***	0.277***	0.003***	0.039	0.556***	0.032***	0.127***	0.198***	0.025***
	0.003	0.061	0.001	0.006	0.001	0.036	0.004	0.004	0.027	0.005	0.007
lictimp	0.9655***	0.7045***	1.000***	0.678***	0.939***	−0.079	0.459***	1.031***	1.236***	0.737***	0.340***
	0.006	0.137	0.013	0.015	0.013	0.211	0.007	0.069	0.274	0.020	0.101
eci	0.114***	0.017	0.001	0.004	0.003	0.154	−0.001	−0.009	0.036	0.009	−0.038***
	0.031	0.018	0.001	0.005	0.004	0.130	0.001	0.009	0.063	0.005	0.006
ltra	−0.058***	0.114	0.002	−0.004	0.015***	0.934***	0.001	−0.031**	0.056	−0.013	0.067***
	0.016	0.103	0.005	0.006	0.005	0.193	0.002	0.015	0.051	0.009	0.006
_cons	—	−0.020	−0.001	−0.005*	−0.011**	−0.071	−0.004**	0.013	0.054	−0.012*	−0.146**
	—	0.019	0.001	0.003	0.005	0.069	0.002	0.017	0.060	0.006	0.071
_ec	—	−0.123***	0.003	−0.037***	−0.063***	−0.858***	0.020**	0.066	0.514*	−0.054**	−0.702***
	—	0.138	0.013	0.011	0.014	0.170	0.009	0.076	0.315	0.024	0.102

Table 6. PMG-ARDL Estimation Model 2 (Dependent Variable=Ecological Footprint)

Variabel	Long Run (Overall)	Short Run (Overall)	id_1	id_2	id_3	id_4	id_5	id_6	id_7	id_8	id_9
lde	0.5160***	1.6244	-0.1887**	4.6419	-3.0635	0.1082**	13.5653***	2.3068	-1.9925	-0.5738***	-0.1844
	0.0841	1.6704	0.0851	8.8423	2.0985	0.0415	3.0032	1.7904	3.0337	0.0848	1.0529
eci	0.2481***	0.5655	-0.0456	3.686	3.0004	0.0705	-4.5890***	1.5406	2.5139	-0.0039	-1.0647
	0.0581	0.8371	0.0409	4.2038	3.3809	0.0672	0.7882	1.022	4.5504	0.0591	0.8427
lgdppc	-0.0804**	2.1352	-0.0024	6.9857	0.9684	0.2672*	-4.3648**	11.5015***	2.809	0.0059	1.0471
	0.0326	1.5325	0.0705	6.0747	1.1684	0.143	1.727	2.3553	4.0258	0.0779	1.8809
ltra	0.6347***	1.3787	-0.2443	2.0986	-2.0259	0.2281*	10.4782***	1.1307	1.598	-0.7733***	-0.0839
	0.1349	1.2119	0.1555	4.891	2.3534	0.1301	1.712	1.6695	3.1748	0.142	1.4235
_cons	—	28.2170***	2.3196	32.2602**	38.8371***	-0.6703	18.4911***	33.5635***	34.4152***	49.2815***	45.4551***
	—	5.9357	1.5454	12.3914	10.5068	2.8562	4.1654	5.8511	8.9126	6.6961	10.8048
_ec	—	-0.9307***	-0.1558	-1.0881**	-1.2550***	0.0216	-0.6371***	-1.0547***	-1.1387***	-1.5912***	-1.4777***

	—	0.1869	0.1028	0.4099	0.3385	0.0951	0.1417	0.1805	0.2949	0.1916	0.3477

Source: Author's computation (2025)

Discussion

Digital Trade, Structural Capabilities, and the Rise of the Digital Economy in OIC Asia

The PMG–ARDL estimates confirm that ICT exports, ICT imports, and economic complexity exert strong and significant positive effects on the digital economy across OIC Asian countries, while trade ratio exerts a significant negative long-run effect. These findings strongly reinforce the argument that digital trade (through both export capability and import-driven technology absorption) serves as a core engine of digital transformation (Abdi & Muhumed, 2025; Jianguo et al., 2025; Riaz et al., 2025). The significant role of complexity supports evidence that countries with diversified, knowledge-intensive production structures are better positioned to scale digital ecosystems (Bentaleb et al., 2024; Tiwari et al., 2025; Y. Wang et al., 2023). Meanwhile, the negative long-run coefficient on trade ratio mirrors studies showing that countries relying on commodity-heavy or low-tech trade structures often experience diversion of fiscal and investment resources away from digital upgrading (Qayyum et al., 2024; Rana et al., 2024; Touati & Ben-Salha, 2024). This aligns with findings that unbalanced trade integration without complementary structural transformation generates limited technological spillovers in emerging economies (Aluko et al., 2023; Bashir et al., 2023; Kazemzadeh et al., 2023). Collectively, the results suggest that in OIC Asia, digital upgrading is driven not by trade volume per se but by *what* is traded (ICT goods/services) and *how* production systems are structured. In practical terms, policies should prioritize high-tech trade agreements, digital export capacity, and capability enhancement. Within Islamic economic ethics, enhancing digitalization that improves efficiency, reduces information barriers, and promotes equitable access aligns with the principles of stewardship and maslahah, ensuring that innovation benefits society sustainably.

Digitalization, Structural Complexity, and Trade: Their Environmental Consequences

Model 2 results indicate that the digital economy, economic complexity, and trade ratio significantly increase ecological footprint in the long run, while GDP per capita reduces environmental pressure. The positive ecological impact of digitalization aligns with findings that early-stage digital transitions raise energy use, device-related waste, and material throughput (Bieser et al., 2024; Pata & Erdogan, 2025; Zhang et al., 2025). Economic complexity's significant positive effect mirrors evidence that complex industrial systems tend to intensify ecological demands through diversified production lines and resource-intensive inputs unless supported by green innovation (Abid & Gafsi, 2025; Kazemzadeh et al., 2023; Latif et al., 2023). The strong positive effect of trade ratio is consistent with literature showing that trade-driven production in emerging economies) especially those integrated into resource- or energy-intensive supply chains (exacerbates ecological footprints (Ghosh et al., 2024; Imran et al., 2024; Sultanova et al., 2024). Conversely, the negative long-run effect of GDP per capita reflects the environmental improvement associated with higher income, improved regulations, advanced cleaner technologies, and structural upgrading (ElMassah & Hassanein, 2023; Junsheng et al., 2024; Q. Wang, Wang, et al., 2024). These dynamics suggest that OIC Asian economies remain in the stage where economic and digital expansion impose substantial ecological burdens. This aligns with prior findings from Arslan et al. (2023) and Latif et al. (2023), which emphasize that the absence of green governance mechanisms amplifies environmental stress during transformation phases. The empirical evidence highlights an urgent need for harmonizing digital and trade policies with sustainability-oriented industrial strategies.

Policy Pathways for Balancing Digital Development and Environmental Sustainability

The empirical outcomes offer actionable insights for policy formulation in OIC Asian economies. Since ICT exports, ICT imports, and economic complexity significantly enhance the digital economy, digital policy should emphasize infrastructure strengthening, technology transfer, and capability deepening, consistent with recommendations by Balsalobre-Lorente et al. (2025), Manulusi et al. (2025), and (Jianguo et al., 2025). Yet, the simultaneous positive impact of these variables on ecological footprint signals the need for regulatory interventions related to responsible digital consumption, e-waste management, and energy-efficient digital infrastructure (Acaroğlu et al., 2023; Behera et al., 2024; B. Wang & Chen, 2022). The positive environmental effect of trade ratio indicates that trade reforms must be aligned with environmental efficiency and green production diversification, supporting insights from Tchapchet-Tchouto (2023), Imran et al. (2024), and Özpolat (2022). The negative coefficient on income suggests that long-run ecological improvements can be achieved through growth strategies emphasizing clean technology adoption, energy efficiency, and environmentally responsible consumption (Rafique et al., 2022; Shahzad et al., 2023; Wan et al., 2022). Strengthening green finance, ecological tax incentives, and cross-national technology sharing among OIC members would therefore strengthen sustainable development pathways. These implications echo broader calls for integrated ecological governance across developing regions (Cibulka & Giljum, 2020; Murányi & Varga, 2021; Paravantis et al., 2021).

Islamic Economic Ethics and the Imperative of Ecological Stewardship

Interpreting the empirical findings through Islamic economic ethics reinforces the urgency of balancing digital progress with environmental responsibility. The evidence that digital advancement, complexity, and trade intensify ecological pressures underscores the Islamic concept of mizan, which warns against imbalances caused by excessive consumption or unsustainable technological growth. The ethical principle of khalifah frames humans as trustees obligated to preserve the environment and prevent degradation, aligning with the need to ensure that economic complexity and digital expansion do not produce fasad or environmental harm (Hanif, 2024; Haque, 2023). Income's mitigating effect on ecological footprint supports the maqasid al-shariah objective of pursuing prosperity in ways that protect life, intellect, and wealth, all of which are inseparable from a stable environment (Amiruddin et al., 2024; Aziz et al., 2024). Scholarship in Islamic economics highlights that development must avoid israf and promote sustainability-oriented innovation (Maftoon et al., 2025; Miyan et al., 2025; Mohamed et al., 2025). Thus, the findings collectively affirm that ecological responsibility is not an optional add-on but a moral imperative in Islamic economic governance, urging OIC Asian countries to adopt digital and trade strategies that uphold environmental preservation and intergenerational justice.

CONCLUSION

This study set out to examine how digital trade, structural technological capabilities, economic complexity, income levels, and trade ratio shape both the digital economy and ecological footprint across 9 OIC Asian economies during 2013–2024. The PMG-ARDL results reveal that ICT exports, ICT imports, and economic complexity significantly enhance digital development, whereas trade ratio suppresses it, while ecological pressure intensifies with digital expansion, complexity, and trade ratio, and declines as income rises, thereby partially supporting the proposed hypotheses. These findings carry important practical implications: policymakers must integrate digital transformation with environmental safeguards, strengthen high-tech trade and capability upgrading, regulate resource-intensive digital infrastructures, and design growth strategies rooted in green innovation and efficiency; theoretically, the study enriches the literature by showing that digitalization and complexity yield dual outcomes—technological advancement and environmental strain—within emerging Islamic economies. Despite its contributions, the research is limited by data availability, the regional focus on OIC Asia, and the reliance on a single estimation framework, all of which may constrain generalizability. Future studies should expand country coverage, incorporate additional environmental and institutional variables, and explore alternative dynamic panel approaches to capture nonlinearities and asymmetric effects. Ultimately, this research underscores the urgency of harmonizing digital progress with ecological stewardship, offering empirical evidence and conceptual insight to guide sustainable development pathways in rapidly transforming OIC Asian economies.

REFERENCES

1. Abban, O. J., Rajaguru, G., & Acheampong, A. O. (2025). The spillover effect of economic institutions on the environment: A global evidence from spatial econometric analysis. *Journal of Environmental Management*, *373*. https://doi.org/10.1016/j.jenvman.2024.123645
2. Abdi, A. H., & Muhumed, A. M. (2025). Modelling the marginal effects of energy consumption, ICT, industrialization, and urbanization on environmental sustainability in Somalia: dynamic ARDL and KRLS approaches. *Discover Sustainability*, *6*(1). https://doi.org/10.1007/s43621-025-01027-w
3. Abid, I., & Gafsi, N. (2025). Economic Complexity, Environmental Sustainability, and Technological Integration in Saudi Arabia: Analyzing Long-Term Trends. *International Journal of Energy Economics and Policy*, *15*(3), 669–683. https://doi.org/10.32479/ijeep.18806
4. Acaroğlu, H., Kartal, H. M., & García Marquez, F. P. (2023). Testing the environmental Kuznets curve hypothesis in terms of ecological footprint and CO2 emissions through energy diversification for Turkey. *Environmental Science and Pollution Research*, *30*(22), 63289–63304. https://doi.org/10.1007/s11356-023-26278-w
5. Agyekum, E. B., & Ali, E. B. (2025). Impact of technological innovation on carbon neutrality-systematic and bibliometric review of two decades of research. *Carbon Research*, *4*(1). https://doi.org/10.1007/s44246-025-00197-6
6. Alfehaid, F., Omri, A., & Altwaijri, A. (2024). Impact of ICT diffusion and opportunity entrepreneurship on environmental sustainability in Saudi Arabia. *Heliyon*, *10*(19). https://doi.org/10.1016/j.heliyon.2024.e39009
7. Aluko, O. A., Opoku, E. E. O., & Acheampong, A. O. (2023). Economic complexity and environmental degradation: Evidence from OECD countries. *Business Strategy and the Environment*, *32*(6), 2767–2788. https://doi.org/10.1002/bse.3269
8. Amiruddin, M. M., Haq, I., Anwar, H., & Haris, A. (2024). Reforming Fiqh Al-Bi'ah (Ecological Jurisprudence) based on Islam Hadhari: An Integration Conservation Framework of Muamalah and Culture. *International Journal of Law and Society*, *3*(3), 187–205. https://doi.org/10.59683/ijls.v3i3.99
9. Arslan, A., Qayyum, A., Tabash, M. I., Nair, K., Ullah, M. A., & Daniel, L. N. (2023). The Impact of Economic Complexity, Usage of Energy, Tourism, and Economic Growth on Carbon Emissions: Empirical Evidence of 102 Countries. *International Journal of Energy Economics and Policy*, *13*(5), 315–324. https://doi.org/10.32479/ijeep.14746
10. Aspy, N. N., Voumik, L. C., Esquivias, M. A., Sugiharti, L., Das, M. K., & Pattak, D. C. (2024). Impact of tourism, globalization, and technological patents on ecological footprint in ASEAN countries: static and dynamic panel regression approaches. *Discover Sustainability*, *5*(1). https://doi.org/10.1007/s43621-024-00708-2
11. Ayoungman, F. Z., Shawon, A. H., & Sohail, A. (2025). Analyzing the impact of financial development, human capital and industrial structure on ecological footprints: a PMG-ARDL approach. *Humanities and Social Sciences Communications*, *12*(1). https://doi.org/10.1057/s41599-025-05553-w
12. Aziz, A., Manalu, P., Oktaviandi, W., Apriadi, D., Candri, & Suteja. (2024). SDG's and Maqasid Shariah Principles: Synergies for Global Prosperity. *Journal of Lifestyle and SDGs Review*, *4*(2), e01873. https://doi.org/10.47172/2965-730x.sdgsreview.v4.n02.pe01873
13. Bai, J., Baltagi, B., & Pesaran, H. (2016). CROSS-SECTIONAL DEPENDENCE IN PANEL DATA MODELS: A SPECIAL ISSUE. *Journal of Applied Econometrics*, *31*(1), 1–3. https://doi.org/https://www.jstor.org/stable/26609084
14. Balsalobre-Lorente, D., Nur, T., & Topaloglu, E. E. (2025). Examining the sustainable development process through the economic complexity, technology, urbanization, and renewable energy in D-8 countries. *Quality and Quantity*, *59*(5), 4461–4501. https://doi.org/10.1007/s11135-025-02161-3
15. Bashir, M. A., Dengfeng, Z., Filipiak, B. Z., Bilan, Y., & Vasa, L. (2023). Role of economic complexity and technological innovation for ecological footprint in newly industrialized countries: Does geothermal energy consumption matter? *Renewable Energy*, *217*. https://doi.org/10.1016/j.renene.2023.119059
16. Behera, B., Behera, P., Sucharita, S., & Sethi, N. (2024). Mitigating ecological footprint in BRICS countries:

unveiling the role of disaggregated clean energy, green technology innovation and political stability. *Discover Sustainability*, *5*(1). https://doi.org/10.1007/s43621-024-00378-0
17. Bentaleb, M., Boudine, H., Ameur, M., & Tayebi, M. (2024). Environmental Health and E-Learning: Effects on Students and Teachers. *E3S Web of Conferences*, *477*. https://doi.org/10.1051/e3sconf/202447700019
18. Bieser, J. C. T., Coroamă, V. C., Bergmark, P., & Stuermer, M. (2024). The greenhouse gas (GHG) reduction potential of ICT: A critical review of telecommunication companies' GHG enablement assessments. *Journal of Industrial Ecology*, *28*(5), 1132–1146. https://doi.org/10.1111/jiec.13524
19. Bildirici, M. E., & Kayikçi, F. (2013). Effects of oil production on economic growth in Eurasian countries: Panel ARDL approach. *Energy*, *49*(1), 156–161. https://doi.org/10.1016/j.energy.2012.10.047
20. Cantero-Galiano, J. (2025). A Renewed Approach to the Connection Between Economic Complexity and Environmental Degradation Considering the Energy Innovation Process in the Five Major European Economies. *Sustainability (Switzerland)*, *17*(7). https://doi.org/10.3390/su17072967
21. Celik, A., & Alola, A. A. (2023). Examining the roles of labour standards, economic complexity, and globalization in the biocapacity deficiency of the ASEAN countries. *International Journal of Sustainable Development and World Ecology*, *30*(5), 591–604. https://doi.org/10.1080/13504509.2023.2172475
22. Charfeddine, L., Kahia, M., & Rahman, A. (2025). The role of technologies, finance, and green energies in transforming Middle East and North African environmental sustainability. *Sustainable Futures*, *9*. https://doi.org/10.1016/j.sftr.2025.100574
23. Cibulka, S., & Giljum, S. (2020). Towards a comprehensive framework of the relationships between resource footprints, quality of life, and economic development. *Sustainability (Switzerland)*, *12*(11). https://doi.org/10.3390/su12114734
24. Daoud, J. I. (2018). Multicollinearity and Regression Analysis. *Journal of Physics: Conference Series*, *949*(1). https://doi.org/10.1088/1742-6596/949/1/012009
25. De Hoyos, Rafael E, & Sarafidis, Vasilis. (2006). Testing for Cross-Sectional Dependence in Panel-Data Models. *The Stata Journal*, *6*(4), 482–496. https://doi.org/10.1177/1536867X0600600403
26. Dinda, S. (2004). Environmental Kuznets Curve Hypothesis: A Survey. *Ecological Economics*, *49*(4), 431–455. https://doi.org/https://doi.org/10.1016/j.ecolecon.2004.02.011
27. Ehigiamusoe, K. U., Lean, H. H., Mustapha, M., & Ramakrishnan, S. (2023). Industrialization, globalization, ICT, and environmental degradation in Malaysia: A frequency domain analysis. *Heliyon*, *9*(10). https://doi.org/10.1016/j.heliyon 2023.e20699
28. ElMassah, S., & Hassanein, E. A. (2023). Economic Development and Environmental Sustainability in the GCC Countries: New Insights Based on the Economic Complexity. *Sustainability (Switzerland)*, *15*(10). https://doi.org/10.3390/su15107987
29. Fertő, I., & Harangozo, G. (2025). Trade-offs and synergies when balancing economic growth and globalization for sustainable development goals achievement. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-93360-3
30. Frees, E. W. (1995). Assessing cross-sectional correlation in panel data. *Journal of Econometrics*, *69*(2), 393–414. https://doi.org/https://doi.org/10.1016/0304-4076(94)01658-M
31. Geng, B., Wu, D., Zhang, C., Xie, W., Mahmood, M. A., & Ali, Q. (2024). How Can the Blue Economy Contribute to Inclusive Growth and Ecosystem Resources in Asia? A Comparative Analysis. *Sustainability (Switzerland)*, *16*(1). https://doi.org/10.3390/su16010429
32. Ghosh, S., Adebayo, T. S., Abbas, S., Doğan, B., & Sarkodie, S. A. (2024). Harnessing the roles of renewable energy, high tech industries, and financial globalization for environmental sustainability: Evidence from newly industrialized economies. *Natural Resources Forum*, *48*(4), 1186–1207. https://doi.org/10.1111/1477-8947.12356
33. Global Footprint Network. (2025). *Ecological Footprint Data*. Https://Api.Footprintnetwork.Org/v1/Data/5001/All/BCtot,EFCtot.
34. Hanif, S. (2024). Islamic Perspectives on Environmental Ethics: Balancing Modern Progress with Sustainability. *International Journal of the Universe and Humanity in Islamic Vision and Perspective*, *1*(2), 23–34. https://researchcorridor.org/index.php/IJUHIVP/article/view/37/36

35. Haque, N. (2023). Ecolibrium: The Quranic Paradigm for Global Sustainability. In *Issues in Science and Theology: Global Sustainability: Science and Religion in Dialogue* (pp. 211–219). Springer. https://doi.org/https://doi.org/10.1007/978-3-031-41800-6_20
36. Imran, M., Khan, M. K., Alam, S., Wahab, S., Tufail, M., & Zhang, Z. (2024). The implications of the ecological footprint and renewable energy usage on the financial stability of South Asian countries. *Financial Innovation*, *10*(1). https://doi.org/10.1186/s40854-024-00627-1
37. Jianguo, J., Rasool, Y., & Kashif, U. (2025). Asymmetric Impacts of Environmental Policy, Financial, and Trade Globalization on Ecological Footprints: Insights from G9 Industrial Nations. *Sustainability (Switzerland)*, *17*(4). https://doi.org/10.3390/su17041568
38. Junsheng, H., Mu, Y., Masud, M. M., Akhtar, R., Saif, A. N. M., Islam, K. M. A., & Hafiz, N. (2024). Navigating the nexus: unraveling technological innovation, economic growth, trade openness, ICT, and CO2 emissions through symmetric and asymmetric analysis. *Humanities and Social Sciences Communications*, *11*(1). https://doi.org/10.1057/s41599-024-03092-4
39. Kazemzadeh, E., Fuinhas, J. A., Salehnia, N., & Osmani, F. (2023). The effect of economic complexity, fertility rate, and information and communication technology on ecological footprint in the emerging economies: a two-step stirpat model and panel quantile regression. *Quality and Quantity*, *57*(1), 737–763. https://doi.org/10.1007/s11135-022-01373-1
40. Khan, A., & Ximei, W. (2022). Digital Economy and Environmental Sustainability: Do Information Communication and Technology (ICT) and Economic Complexity Matter? *International Journal of Environmental Research and Public Health*, *19*(19). https://doi.org/10.3390/ijerph191912301
41. Khan, M., & Khan, I. (2024). Achieving environmental sustainability through technological innovation, good governance and financial development: perspectives from low income countries. *Sustainable Futures*, *8*. https://doi.org/10.1016/j.sftr.2024.100392
42. Kor, Md. S. (2024). Navigating the path to environmental sustainability: Insights from CIVETS on the intersection of ICT diffusion, natural resources, and green technological innovation. *PLOS ONE*, *19*(12). https://doi.org/10.1371/journal.pone.0309264
43. Latif, N., Rafeeq, R., Safdar, N., Liaquat, M., Younas, K., & Ahmad, S. (2023). Investigating the role of economic integration and financial development: Rebound effect and green ICT in BRICS. *Sustainable Futures*, *6*. https://doi.org/10.1016/j.sftr.2023.100126
44. Liu, Q., & Mehmood, U. (2025). From pixels to policy: deciphering G-20 countries' digitalization, resource management, external conflicts, governance, and environmental frameworks. *Frontiers in Environmental Science*, *13*. https://doi.org/10.3389/fenvs.2025.1517486
45. Maftoon, A. S., Razzaq, A., Arfeen, M. I., & Khan, K. (2025). The interplay of renewable energy and human capital: Unveiling the moderating pathways to carbon emission mitigation in a global panel study. *Sustainable Futures*, *10*. https://doi.org/10.1016/j.sftr.2025.101108
46. Manulusi, M. R., Madris, u., & Saudi, N. D. S. (2025). Sustainable Development and Environmental Impacts: Insights from Economic Activities in ASEAN-5 Economies. *International Journal of Energy Economics and Policy*, *15*(3), 68–75. https://doi.org/10.32479/ijeep.18624
47. Mehmood, U., Agyekum, E. B., Kotb, H., Milyani, A. H., Azhari, A. A., Tariq, S., Ul-Haq, Z. U., Ullah, A., Raza, K., & Velkin, V. I. (2022). Exploring the Role of Communication Technologies, Governance, and Renewable Energy for Ecological Footprints in G11 Countries: Implications for Sustainable Development. *Sustainability (Switzerland)*, *14*(19). https://doi.org/10.3390/su141912555
48. Miyan, M. S., Cheong, C. W. H., Sharif, A., & Afshan, S. (2025). Greening the future: How green finance and innovation shape environmental sustainability in D-8 nations. *Sustainable Futures*, *10*. https://doi.org/10.1016/j.sftr.2025.101168
49. Mohamed, A. A., Abdi, A. H., Mohamud, S. S., & Osman, B. M. (2025). Institutional quality, economic growth, and environmental sustainability: a long-run analysis of the ecological footprint in Somalia. *Discover Sustainability*, *6*(1). https://doi.org/10.1007/s43621-025-01063-6
50. Monstadt, J., & Saltzman, K. (2025). HOW DATA CENTERS HAVE COME TO MATTER: Governing the Spatial and Environmental Footprint of the 'Digital Gateway to Europe.' *International Journal of Urban and Regional Research*, *49*(4), 757–778. https://doi.org/10.1111/1468-2427.13316

51. Muhamad, G. M., & Khezri, M. (2025). Unveiling the environmental impact of resource Dependency: Developing a resource curse index (RCI) and its effects on carbon, cropland, forest, and fishing footprints. *Journal of Cleaner Production*, *522*. https://doi.org/10.1016/j.jclepro.2025.146326
52. Murányi, A., & Varga, B. (2021). Relationship Between the COVID-19 Pandemic and Ecological, Economic, and Social Conditions. *Frontiers in Public Health*, *9*. https://doi.org/10.3389/fpubh.2021.694191
53. Nadeem, M., Malik, M. I., Adil, S., & Junaid, N. (2023). Exploring the determinants of ecological efficiency in selected emerging economies using pooled mean group estimator. *Regional Statistics*, *13*(2), 352–368. https://doi.org/10.15196/RS130207
54. Neagu, O., & Neagu, M.-I. (2022). The Environmental Kuznets Curve revisited: Economic complexity and ecological footprint in the most complex economies of the world. *Studia Universitatis Vasile Goldis Arad, Economics Series*, *32*(1), 78–99. https://doi.org/10.2478/sues-2022-0005
55. Nkoro, E., & Uko, A. K. (2016). Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation. *Journal of Statistical and Econometric Methods*, *5*(4), 63–91.
56. Noorzai, M. T., Bełdycka-Bórawska, A., Kutlar, A., Rokicki, T., & Bórawski, P. (2025). Exploring the Link Between Energy Consumption, Economic Growth, and Ecological Footprint in the Major Importers of Poland Energy: A Panel Data Analysis. *Energies*, *18*(13). https://doi.org/10.3390/en18133303
57. Olayungbo, D. O., & Quadri, A. (2019). Remittances, financial development and economic growth in sub-Saharan African countries: evidence from a PMG-ARDL approach. *Financial Innovation*, *5*(1). https://doi.org/10.1186/s40854-019-0122-8
58. Onyeneke, R. U., Chidiebere-Mark, N. M., Ejike, R. D., Chikezie, C., & Uhuegbulem, I. J. (2024). Determinants of Environmental Quality in Africa. *Ekologia Bratislava*, *43*(2), 202–213. https://doi.org/10.2478/eko-2024-0021
59. Oprea, S.-V., Bâra, A., & Georgescu, I. A. (2025). Assessing the Dynamics of Ecological Footprint in Relation to Economic and Energy Factors: A Comparative Analysis of Finland and Japan. *Journal of the Knowledge Economy*, *16*(3), 11162–11197. https://doi.org/10.1007/s13132-024-02312-1
60. Özpolat, A. (2022). How does internet use affect ecological footprint?: An empirical analysis for G7 countries. *Environment, Development and Sustainability*, *24*(11), 12833–12849. https://doi.org/10.1007/s10668-021-01967-z
61. Paravantis, J. A., Tasios, P. D., Dourmas, V., Andreakos, G., Velaoras, K., Kontoulis, N., & Mihalakakou, P. (2021). A regression analysis of the carbon footprint of megacities. *Sustainability (Switzerland)*, *13*(3), 1–26. https://doi.org/10.3390/su13031379
62. Pata, U. K., & Erdogan, S. (2025). Technological progress, institutions, and environment: A disaggregated ecological footprint analysis for Gulf Cooperation Council countries. *Sustainable Futures*, *10*. https://doi.org/10.1016/j.sftr.2025.100925
63. Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. *Journal of the American Statistical Association*, *94*(446), 621–634. https://doi.org/10.1080/01621459.1999.10474156
64. Qayyum, M., Zhang, Y., Ali, M., & Kirikkaleli, D. (2024). Towards environmental sustainability: The role of information and communication technology and institutional quality on ecological footprint in MERCOSUR nations. *Environmental Technology and Innovation*, *34*. https://doi.org/10.1016/j.eti.2023.103523
65. Rafique, M. Z., Nadeem, A. M., Xia, W., Ikram, M., Shoaib, H. M., & Shahzad, U. (2022). Does economic complexity matter for environmental sustainability? Using ecological footprint as an indicator. *Environment, Development and Sustainability*, *24*(4), 4623–4640. https://doi.org/10.1007/s10668-021-01625-4
66. Rana, F., Hussain, B., Nassani, A. A., Hussain, A., Haffar, M., & Naqvi, S. A. A. (2024). Contribution of hydro energy production, economic complexity and technological innovation in achieving an environmentally sustainable Asia. *Geoscience Frontiers*, *15*(5). https://doi.org/10.1016/j.gsf.2024.101876
67. Riaz, M. H., Alam, M., Ali, A., Ahmed, Z., Uddin, M. S., & Raihan, A. (2025). Resource-Driven industrialization and economic growth in BRICS+: A pathway to sustainability or environmental tension? *Sustainable Futures*, *10*. https://doi.org/10.1016/j.sftr.2025.101136

68. Ridwan, R. L., Alomair, A., & Al Naim, A. S. (2024). How Financial Development Is Driving the Growth and Environmental Dimensions of Sustainable Development in Africa: Heterogeneous Analyses. *Sustainability (Switzerland)*, *16*(21). https://doi.org/10.3390/su16219284
69. Shahzad, U., Elheddad, M., Swart, J., Ghosh, S., & Doğan, B. (2023). The role of biomass energy consumption and economic complexity on environmental sustainability in G7 economies. *Business Strategy and the Environment*, *32*(1), 781–801. https://doi.org/10.1002/bse.3175
70. Sultanova, G., Djuraeva, R., Ahmedov, A., & Turaeva, S. (2024). Does Export Diversification Matter for Ecological Footprint in Uzbekistan? Empirical Evidence from ARDL Approach. In Y. Sang, A. Satyanaga, & E. Kuzmin (Eds.), *E3S Web of Conferences* (Vol. 574). EDP Sciences. https://doi.org/10.1051/e3sconf/202457404004
71. Tang, Y., Yasin, I., & Ul Rehman, K. (2024). Time-Varying Impacts of Monetary Policy and Socio-Economic Factors on China's CO2 Emissions and Ecological Footprint: A Multi-Methodological Analysis. *Sustainability (Switzerland)*, *16*(24). https://doi.org/10.3390/su162410808
72. Tchapchet-Tchouto, J.-E. (2023). An empirical assessment on the leveraging evidence of economic complexity under environmental kuznets curve hypothesis: A comparative analysis between Nordic and Non-Nordic European countries. *Innovation and Green Development*, *2*(4). https://doi.org/10.1016/j.igd.2023.100074
73. Tiwari, S., Sharif, A., Sofuoğlu, E., & Nuţă, F. (2025). A step toward the attainment of carbon neutrality and SDG-13: Role of financial depth and green technology innovation. *Research in International Business and Finance*, *73*. https://doi.org/10.1016/j.ribaf.2024.102631
74. Touati, K., & Ben-Salha, O. (2024). Reconsidering the Long-Term Impacts of Digitalization, Industrialization, and Financial Development on Environmental Sustainability in GCC Countries. *Sustainability (Switzerland)*, *16*(9). https://doi.org/10.3390/su16093576
75. Wan, X., Jahanger, A., Usman, M., Radulescu, M., Balsalobre-Lorente, D., & Yu, Y. (2022). Exploring the Effects of Economic Complexity and the Transition to a Clean Energy Pattern on Ecological Footprint From the Indian Perspective. *Frontiers in Environmental Science*, *9*. https://doi.org/10.3389/fenvs.2021.816519
76. Wang, B., & Chen, T. (2022). Social Progress beyond GDP: A Principal Component Analysis (PCA) of GDP and Twelve Alternative Indicators. *Sustainability (Switzerland)*, *14*(11). https://doi.org/10.3390/su14116430
77. Wang, C., & Uctum, M. (2024). Ecological footprint of FDI inflows and income threshold effect: New results with a new approach to income classification. *Environmental and Sustainability Indicators*, *22*. https://doi.org/10.1016/j.indic.2024.100356
78. Wang, Q., Li, Y., & Li, R. (2024). Ecological footprints, carbon emissions, and energy transitions: the impact of artificial intelligence (AI). *Humanities and Social Sciences Communications*, *11*(1). https://doi.org/10.1057/s41599-024-03520-5
79. Wang, Q., Wang, X., Li, R., & Jiang, X. (2024). Reinvestigating the environmental Kuznets curve (EKC) of carbon emissions and ecological footprint in 147 countries: a matter of trade protectionism. *Humanities and Social Sciences Communications*, *11*(1). https://doi.org/10.1057/s41599-024-02639-9
80. Wang, Y., Qamruzzaman, M., & Kor, Md. S. (2023). Greening the Future: Harnessing ICT, Innovation, Eco-Taxes, and Clean Energy for Sustainable Ecology—Insights from Dynamic Seemingly Unrelated Regression, Continuously Updated Fully Modified, and Continuously Updated Bias-Corrected Models. *Sustainability (Switzerland)*, *15*(23). https://doi.org/10.3390/su152316417
81. Wu, J., Yu, H., Cao, N., Zhang, J., Khan, J., & Lee, D. (2025). Ecological footprint analysis as a tool for advancing sustainable development goals (SDGs): Evidence from China. *Ecological Indicators*, *176*. https://doi.org/10.1016/j.ecolind.2025.113653
82. Wu, T., Rocha, J. C., Berry, K., Chaigneau, T., Hamann, M., Lindkvist, E., Qiu, J., Schill, C., Shepon, A., Crépin, A.-S., & Folke, C. (2024). Triple Bottom Line or Trilemma? Global Tradeoffs Between Prosperity, Inequality, and the Environment. *World Development*, *178*. https://doi.org/10.1016/j.worlddev.2024.106595
83. Zhang, H., Qamruzzaman, M., & Monsur Mindia, P. (2025). Unveiling the dynamic connection: ICT,

technological innovation, financial inclusion, natural resources, and environmental degradation in MENA countries: evidence from CS-ARDl and NARDL. *Frontiers in Environmental Science*, *13*. https://doi.org/10.3389/fenvs.2025.1541556

84. Zinngrebe, Y., Berger, J., Bunn, C., Felipe-Lucia, M. R., Graßnick, N., Kastner, T., Pe'Er, G., Schleyer, C., & Lakner, S. (2024). Prioritizing partners and products for the sustainability of the EU's agri-food trade. *One Earth*, *7*(4), 674–686. https://doi.org/10.1016/j.oneear.2024.03.002